

Load forecasting and Load Management in Smart Grids Using NSGA-II Optimized ANN Model

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Abstract — Precise prediction of residential power consumption, and effective management of load are important tasks in smart grid. The current research proposes a novel hybrid model of ANN with NSGA-II to solve the multi-objective optimization problems for smart grid operations. The model incorporates four important inputs to simultaneously predict forecast demand and load management reliability: time-of-day, temperature, consumer type, and historical load. The ANN model optimized by NSGA-II offers improved forecasting, resulting in the best fitness value of 855.176 kWh, and the resulting high correlation coefficient $R = 0.97432$ for the load forecasting. Meanwhile, the model also maintained a high level of load management reliability as present an best Fitness 86.7012 % and a correlation $R = 0.93381$. Pareto front analysis demonstrated a trade-off solution between forecast accuracy (855.928–855.934 kWh) and reliability (84.043% to 84.086%) and therefore it is flexible in advising grid operator. This NSGA-II-ANN hybrid approach has wide range of applications for real-time load prediction, and better resource allocation and control for increasing smart grid stability in dynamic operation condition.

Keywords— Smart Grid Forecasting, NSGA-II Algorithm, Artificial Neural Network (ANN), Load Management Reliability, Power Demand Prediction.

I. INTRODUCTION

Growing worldwide demand for electrical energy due to new technologies, industrialization and urbanization has created enormous pressure for modern power systems. Accurate prediction of consumer power demand is critical for the effective management of smart grids, in which both sources and consumers are variable [1]. The demand prediction is important not just for system stability, but also for economic steadiness of power generation, distribution, and load control. There have been investigations on the use of Multi-Objective Optimization algorithms including NSGA II as they have had efficient performance in dealing with complex conflicts between objectives. NSGA-II provides a strong evolutionary computing technique for optimizing multiple objectives, e.g., minimizing prediction error and maximising system reliability concurrently [5].

Power demand prediction has been extensively analyzed in previous works through different methodologies spanning from statistical procedures to advanced machine learning procedures. Autoregressive Integrated Moving Average (ARIMA), Combination of Exponential Smoothing and ARIMA, Support Vector Machines (SVM) have shown fair prediction under static conditions while poor performance is seen in the presence of nonlinearity and multi-factored dependencies. In recent years Artificial Neural Networks (ANN) are successfully placed in the models for load

forecasting because of their ability to learn from complex patterns in historical data [7]. For instance, Khosravi et al. [8] proved that ANNs may be more accurate than statistical models in short-term demand forecasting when time series are very noisy. Similarly, Zhang et al. [9], developed RNN-based real-time demand forecasting, which generated enhanced prediction performance for different load variations. Yet only few works have considered the problem as an actual multi-objective optimization problem.

The following research gap were identified

- Lack of integrated models combining ANN forecasting with NSGA-II Multi objective optimization.
- Limited inclusion of consumer segmentation (residential, commercial, and industrial) in forecasting models. Absence of explicit load management reliability metrics as secondary optimization target.

II. METHODOLOGY

Figure 1 represents, the proposed methodology starts with Data Input, raw form of system networks is obtained. This is being Data Preprocessed and removing any noise in wanted and missing data in wanted and normalization of the data for further process. During the Feature Selection, the four essential inputs are identified: (i) time of the day, (ii) temperature, (iii) consumers type and, (iv) historical load. These processed characteristics are input to the ANN Forecasting Model and the

predictive load demand is obtained. The forecast results are post-processed by NSGA-II Optimization, which addresses the forecasting accuracy and the load management reliability. The optimal outputs (Pareto Front) provide multiple feasible trade-off solutions. Lastly, such outputs can be used to assist in real time decision making Decision Support systems.

The main goal of the optimization routine of the work is to figure out the best minimal set of parameter values at which the forecasting error and the load management dependability are minimized. The following corresponding objective functions to minimize the forecasting errors and maximize the reliability of the load management are mathematically expressed as Eq. [1] and Eq. [2], respectively. These functions are obtained by regression analysis carried out on the basis of experimentally determined values. The MATLAB (R2021a) with Genetic Algorithm (GA) toolbox was interfaced to predict forecast error and load management reliability under uncertainty of inputs.

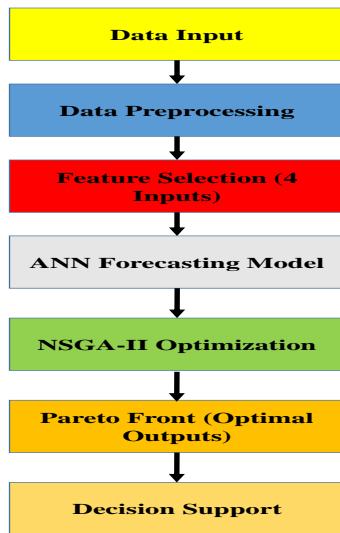


Fig 1. Flowchart of the Integrated ANN-NSGA-II Framework for Load Forecasting and Multi-Objective Optimization.

The input parameters were optimized using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) aiming 10 to achieve better performance indices. At each iteration a fixed population (the number of chromosomes) were treated such that the chromosomes encoded the process parameters, (time-of-day (x_1), temperature (x_2), type of consumer (x_3) and previous loads (x_4) respectively. These encoded parameters were compared iteratively to find the optimal parameters set by NSGA-II. In 20 order to test the robustness and reproducibility of the optimisation, 27 multiple simulation runs were performed with

the same NSGA-II settings. The predictive model performance was validated by comparing the simulated mean values with experimentally verified test data obtained by the predicted optimum input parameters. Table 1, represents the Genetic Algorithm parameters certain for the current problem.

Table 1. The Genetic Algorithm parameters certain for the current problem

Population size	200
Number of generations	600
Crossover Probability	0.95
Mutation Probability	0.05

2. Fitness function

The genetic algorithm employs the mathematical model developed using Minitab statistical software 2021 version, wherein the formulated linear regression equations serves as fitness function for the optimization process.

Fitness Function of Forecasted Demand

$$Y(1) = (855 + 0.2857*X(1) + 0.28*X(2)+ 0.1*X(3) + 0.992*X(4));$$

2.2.2. Fitness Function of Reliability Index Eq..[1]

$$Y(2)= (86 + 0.2221*X(1)+ 0.35*X(2) + 0.3*X(3) + 0.1055*X(4)); Eq..[2]$$

3. Artificial Neural Network Modeling and Simulation

The development of the Artificial Neural Network model was carried out using MATLAB R2021b. Table 2, represents a comprehensive summary of the optimized network architecture and configuration parameters employed for the ANN. The hidden layer within the network are responsible for extracting complex features from the input dataset, enabling the model to effectively capture nonlinear relationship and establish accurate mappings between the input variables and corresponding outputs.

Table 2. Optimum setting of the artificial neural network

ANN parameters setting for experiments	
ANN network category	Feed forward back propagation
Network learning function	LEARNGDM
Function used for performance	MSE

Function used for training	TRAINLM
Transfer function	Tansig/Purelin
Neurons used	20

III. RESULTS AND DISCUSSION

1. Fitness curve for forecast demand as objective 1, objective 2 and its Pareto Front

The fitness curve describes convergence of the NSGA-II algorithm for minimum demand power forecast error estimation as shown in Figure 2(a). The x and y axes correspond to the generation number (from 0 to 400), and fitness (kWh) respectively. Two fitness measures are displayed: the Best fitness (black) and the Mean fitness (blue). The generation zero in the prediction model has higher fitness values (above 14 860 kWh) because of higher prediction errors due to ANN with random initialization of its parameters. With the progress of the optimization, there is large decrease in the best and mean fitness in the first 50 generations, which manifests the good searching ability of NSGA-II in the early stage of evolution. Beyond generation 50, the two curves converge, suggesting the convergence to “good” solutions. 855.176 kWh is the final Best fitness obtained, the Mean fitness of the last population lays at 855.266 kWh. This slight disparity between the best and mean demonstrates that the population is well-converged and remains quite stable in those region decreasing the noise between candidates. This result confirms that NSGA-II was performing well in minimizing the forecast error (Objective 1), such that the parameters of the ANN model have been well-tuned to the accurate demand forecasting, something that is essential in the reliable operation of smart grid.

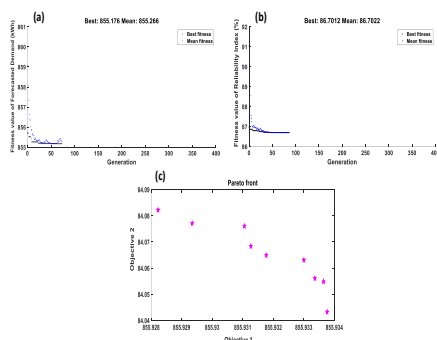


Fig 2. Fitness Convergence Curve of NSGA-II, a) Forecasted Demand Optimization and b) Reliability Index Optimization, c) Pareto Front Obtained from NSGA-II Optimization Representing Trade-off between

Forecasted Demand (Objective 1) and Reliability Index (Objective 2)

The fitness plot in Figure 2(b), shows the optimization of NSGA-II to maximize the Load Management Reliability Index that is vital to maintain stability and efficiency of smart grid. The x-axis represents the generation (with a range from 0 to 400), while the y-axis shows the percentage (%) of the fitness reliability index values. Results in two curves:: best fitness (black) and mean fitness (blue). In the first generated population (generation 0), both best and mean fitness values begin at greater than 91%, suggesting a widely dispersed population with significant variation in solution quality. In the course of generations, a steep slope at the beginning of the line (e.g., the first 50 generations) is visible, showing that the early exploration is quickly increasing the quality of the solution by dealing with more stable forecasting configurations. After cycle 50, the curves level off, which is showing the convergence to the optimal reliability values. The Best fitness obtained at last is 86.7012% and the Mean fitness is 86.7022%, indicating good convergence for the population.

The Pareto Front shown in the Figure 2(c), describes the trade-off results of Objective 1 and Objective 2. The X-axis indicates the Objective 1 values from 855.928 to 855.935 KWh, and the Y-axis shows the Objective 2 values from 84.04% to 84.09%. Every point of magenta is a non-dominated solution obtained by the NSGA-II algorithm. The Pareto front has a gentle negative gradient which signals a trade off between the two objectives: the less the accuracy of a forecast (on the left in the x-axis), the declining tendency of reliability index (in the y-axis). This validates the multi-objective property of the problem in which the enhancement of one objective comes at a marginal trade-off for the other. The maximum and minimum reliability are 84.086% (a forecasting error of 855.928 kWh) and 84.043% (a forecasting error of 855.934 kWh), respectively.

3. ANN model Architecture for present research work

The model architecture configuration used for forecasting in this study is also demonstrated in the Figure 3, it was built in the MATLAB R2021a version Neural Fitting Tool (nftool). The model is constructed with 4 input neurons representing the four selected features: time of day, temperature, consumer type, and historical load. A hidden layer with 20 neurons is used to allow the network to learn nonlinear relationships 8 between input parameters and output targets. The output layer has 2 neurons, generating two outputs are forecasted power demand and load management reliability index. The network is a feed forward W and b trained to minimize prediction error. This setup is the most important for the research, as it directly affects the

prediction accuracy and optimization performance. Such 20 hidden neurons trade-off the model complexity and generalization, such that the ANN is able to learn complex patterns and avoid being overfit, which are necessary for producing reliable and stable multi-criteria forecasting results.

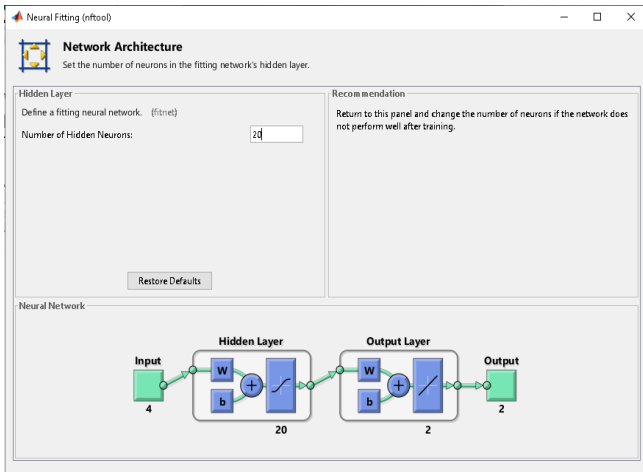


Fig 3. Neural Network Architecture for Load Forecasting Model Using MATLAB

3. Mean squared error plot and error histogram for objective 1 and objective 2

Figure 4(a) is the training performance of the ANN forecasting model developed in minimizing forecasting error for Objective 1. The number of training epochs is ranging from 0 to 6 in x-axis and the y-axis is showing mean squared error (MSE) as its measure for the prediction fitness, on a log scale. Blue, green, and red curves are the MSE for training, validation and testing data. The best validation performance is indicated by the green dotted line. The model presented early convergence as well as good generalization capability from the ideal performance obtained at epoch 1 (MSE = 0.22241), to the favourable network initialization and the adequate data pre processing. This plateau trend is reflecting the model's ability to generalize to unseen data, without overfit on the training data. The low gap between validation and test performances suggests the ability of the 6 ANN to guarantee the forecasting accuracy on new data. This figure verifies that the architecture effectively captures the complex nonlinear relationships in the data with very limited number of iterations which in turns satisfies the Objective 1 by providing accurate predictions on the power demand. The optimal validation early stopping avoids the overfitting of the model and has good prediction accuracy development, training and validation, performance evaluation, and results.

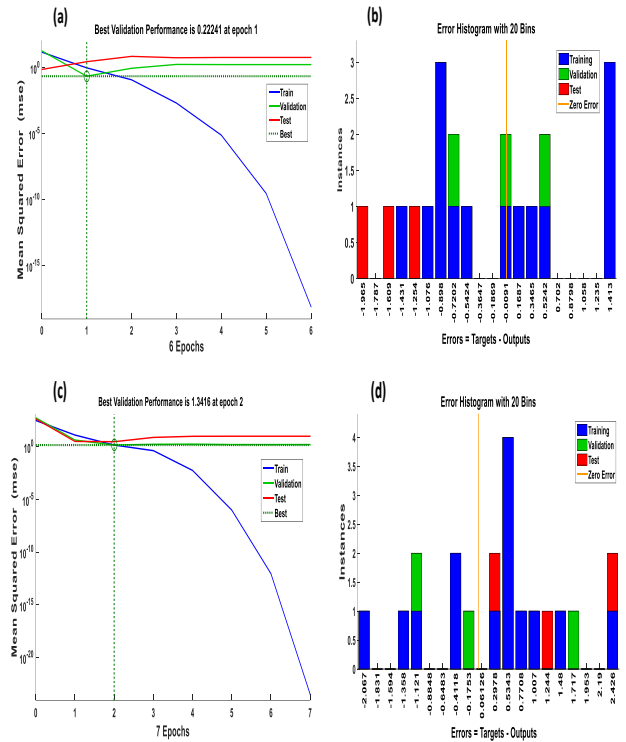


Fig 4. ANN Training Performance Curve for Objective 1 (Forecasted Demand), a) Best Validation Performance of 0.22241 at Epoch 1, b) Error Histogram for ANN Model Performance on Objective 1 (Forecasted Demand), c) Best Validation Performance for Objective 2 (Reliability Index) 1.3416 at Epoch 2, d) Error Histogram for ANN Model Performance on Objective 2 (Reliability Index)

The error histogram expresses the distribution of prediction errors of ANN model to predict the power demand, which is directly associated with Objective 1 as discussed in Figure 4(b). The x-axis represents the error (value of Targets – value of Outputs) between -1.956 and 1.413, and the y-axis the number of examples for each error. The data are partitioned into training (blue), validation (green), and test (red) datasets. The large majority of errors are concentrated close to zero error (orange line), confirming high model correctness. There is a peak around the -0.898 and -0.720 error bins, with 3 instances for training and 2 for validation, indicating a slight under-prediction in some cases. A handful of extreme errors appears outside ± 1.5 , implying few large differences. The narrow and symmetric curve reflects good generalization and low bias for all constellations. This figure is the key one as it suggests from a visual perspective that the ANN models retains consistent forecasting power as most of the forecasts are very close to the actual demand values, validating the fulfilment of the Objective 1.

The model training achievement of the ANN model for the optimization of the load management reliability index is shown in the Figure 4(c), which is directly related to Objective 2. The x-axis and y-axis indicate 24 epochs (0 to 7) and mean squared error (MSE) in a logarithmic scale, respectively. The model has reached its best validation loss of 1.3416 at epoch=2, green dotted lines. The training error (blue curve) still keeps dropping significantly starting epoch 2, even to values near 10^{-20} , but both validation (green) and test (red) curves from epoch 2 are largely leveling out. This suggests that the model is able to learn the underlying patterns and also generalize without too much over fitting. The larger MSE in reliability (rather than forecast error) is indicative of the difficulty and nuance in forecasting the load management stability. This shows that learning-generalization equilibrium and high reliability performance which is essential for gate stability and to satisfy those Objective 2 is achieved by the NSGA-II optimized ANN model.

Figure 4(d), Error Histogram shows the distribution of prediction errors for the load management reliability index for Objective 2. On the x-axis is targets outputs and that statistic goes from -2.067 to 2.426, and on the y-axis there is the count of each bin. Training (blue), validation (green) and testing (red) data sets are plotted along 20 bins, and the orange line represents the zero error. There is a cluster of errors between -0.4118 and 0.5343, and the highest peak is 0.5343 which occurs 4 times. This suggests that, on average, most predictions underestimate, but not by a significant amount (though the deviation is positive, for most predictions). There are only a handful of cases above the dome level of error of 2.426 or so, indicating seldom pathological deviations. This distribution indicates that the predictions of the ANN model are reliable among all the datasets with acceptable errors. Despite enhancements in robustness under the forecast error with the slight increase in error spread, the model preserves generalization to optimize load management reliability which is vital to maintain grid stability at real time operation and effectively for realization of Objective 2.

4. Regression Performance Plots for ANN Model of objective 1 and objective 2

The regression plot(s) in Figure 5, describes the actual target value versus the predicted output for both forecasting and reliability features. Figure (5a) depicts the Objective 1 (Forecasted Demand), and Figure (5b) shows the Objective 2 (Reliability Index). In Figure (5a), the predicted power demand outputs are close to the target values with regression equation $\text{Output} = 0.93 \times \text{Target} + 48$ and a high coefficient of correlation $R = 0.97432$. The present study shows that there can be good ANN model prediction due to high degree of scatter 17

demonstrated by the values of the prediction model for ANNs which not deviate to a greater extent as the $X = 55 Y$ line. Figure (5b) (Objective 2) represents the performance of ANN model for predicting the reliability index of the load management. The correlational regression equation, $\text{Output} \approx 1.3 \times \text{Target} - 31$ ($R = 0.93381$) is also of a high and very slightly lower correlation than Objective 1, which suggests acceptable prediction accuracy for reliability optimization. These strong correlation coefficients show that more importantly, the optimized ANN model of the NSGA-II is able to learn and infer that complex nonlinear relationship for the two objectives. This behaviour is crucial to meet the research objective: high quality load forecast and stable load management for the effective smart grid operations.

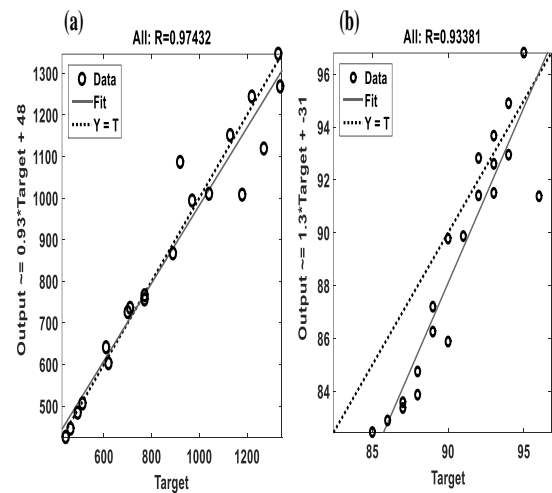


Fig 5. Regression Performance Plots for ANN Model: (a) Load Forecasting Accuracy ($R = 0.97432$), (b) Load Management Reliability ($R = 0.93381$)

IV. CONCLUSION

This study has proposed a hybrid forecasting model based on ANN and NSGA-II that had been developed 23 successfully as a forecasting tool for multi-objective optimization in smart grid operations. The model 11 incorporated four principal input factors born, namely time of day, temperature, consumer category, and historical load, in order to estimate both the forecasted power demand and the reliability of the load management. For Objective 1, the model produced a good forecasting with a low predicting error resulted the best fitness value of 855.176 kWh, and a high correlation coefficient $R = 0.97432$. At the same time, for Objective 2, the system had high

reliability, achieving a best reliability index of 86.7012% with corresponding $R = 0.93381$. The NSGA-II optimization has successfully balanced the trade-offs, as the Pareto front analysis falls within the range from 855.928 to 855.934kWh for forecast error and 84.043% to 84.086% for reliability. This multi-objective optimization approach provides the utilities with optimal solutions when considering the operational priorities. The proposed model has numerous applications in real-time load prediction, optimal load distribution, resource scheduling and smart grid stability improvement.

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